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Evaluating airline service quality through a comprehensive text-mining and multi-criteria decision-making analysis

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ABSTRACT

Service quality is of paramount importance for the long-term sustainability of the airline industry, which is characterized by intense competition. However, previous research in this field has frequently been limited by shortcomings in sample size, efficiency, and dependability. This study addresses these deficiencies by introducing refined insights and establishing a comprehensive yet highly elucidative ranking framework. Initially, we employ Latent Semantic Analysis (LSA) to distill principal themes and sentiments from online reviews of 80 airlines. Subsequently, we employ the SentiWordNet lexicon and the TextBlob package for sentiment analysis based on the aforementioned reviews. Following this, we construct a hierarchical structure using the computation of compromise solutions, employing an integrated Technique for Order Preference by Similarity to Ideal Solution, vis-à-vis Kriterijumska Optimizacija I Kompromisno Resenje-Adversarial Interpretive Structural Model (TOPSIS-VIKOR-AISM) methodology. Finally, the ranking of airlines from best to worst based on perceptions gained from online reviews provides an immediate visualization solution. This study not only assists consumers in making informed decisions but also provides airlines with insights that can be used to enhance their service offerings. The study presents novel insights into the assessment of service quality, with potential applicability to the airline industry and beyond.

1. Introduction

Airline service quality has a significant impact on a company's profitability and sustainability in the highly competitive aviation industry Haghighat (2017), Li (2017), Mousavi and Bossink (2020), Shadiyar et al. (2020), Bakır and Atalık (2021) and Badanik et al. (2023). It is evident that consumers are acutely sensitive to a number of factors, including airline reputation (Park et al., 2004), loyalty programmes (Jiang and Zhang, 2016), safety standards (Baisya and Sarkar, 2004) and punctuality (Elliott and Roach, 1993). In order to maintain and enhance their reputation, airlines must fully comprehend customer expectations and deliver exemplary services (Duncan et al., 2017). This conundrum of decision-making is primarily encountered by airline service managers and policy-makers who strive to achieve a balance between customer satisfaction and operational efficiency. While numerous quality rankings are derived from consumer surveys, the availability of such surveys is limited, and they often suffer from subjectivity, inconsistent standards, and challenging comparability.

To navigate the intricacies of decision-making in service quality ranking, scholars have increasingly adopted multi-criteria decision-making (MCDM) methodologies. MCDM, a subfield of operations research, addresses complex decision-making challenges involving multiple, sometimes conflicting, criteria (Taherdoost and Madanchian, 2023). It is incumbent upon airline executives and stakeholders to identify the most pertinent criteria from the customer's perspective. MCDM enables the evaluation and comparison of alternatives based on their performance across various criteria, thereby facilitating the selection of the optimum or most favored option in accordance with a defined preference model (Sahoo and Goswami, 2023). The practical applications of MCDM extend to a diverse range of domains, including occupational health risk evaluation (Thokala et al., 2016), supply chain network analysis (Gul, 2018), and decision-making in healthcare scenarios (Das et al., 2022). However, traditional MCDM methods are constrained by a number of challenges, including the limited availability of data and inefficiencies in ranking mechanisms, lack of ranking stability, and an over-reliance on historical quantitative data (Sotoudeh-Anvari, 2022).

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In light of these challenges, there is an urgent necessity to augment traditional MCDM approaches by incorporating supplementary information sources. Text-mining techniques, in recent developments, have proven to be invaluable for gleaning insights from extensive textual datasets (Antons et al., 2020; Hassani et al., 2020). In particular, researchers in the field of aviation service quality assessment have employed text mining techniques to analyze customer reviews, feedback and sentiments, as evidenced by the works of Lucini et al. (2020), Kumar et al. (2021). In addressing the challenges of decision-making in the airline industry, regulators and operational managers are increasingly turning to MCDM methodologies in order to discern the most impactful service quality factors from the customer's viewpoint. The qualitative aspect, when combined with MCDM, enhances the decision-making framework by capturing nuances that may be overlooked by purely quantitative data analysis (Hashemkhani Zolfani and Derakhti, 2020).

In the field of service quality rankings, the integration of text-mining techniques with MCDM has yielded insightful studies. For example, Park (2023) combined data envelopment analysis with text mining to analyze online text reviews and evaluate customer satisfaction for the top 20 global airlines in 2020. Similarly, Singh et al. (2022) combined text mining methods such as sentiment analysis and topic modeling to analyze the impact of service quality captured through customer reviews of logistics service providers on different operational, financial and aggregate performance. Eshkevari et al. (2022) integrated semantic mining and MCDM to design an end-to-end ranking method to rank the quality of hotel services, facilities, and amenities based on customer reviews.

The research project has three main objectives. Firstly, it aims to explore the crowd wisdom (Prelec et al., 2017) evident in tens of thousands of online reviews. Secondly, it provides airlines with insights into current business issues. Thirdly, it provides customers with a clear and comprehensive ranking list of airline service quality. In more detail, the project makes the following contributions: (i) Using text mining and sentiment analysis techniques to extract tens of thousands of online airline service reviews in different languages, which may be the largest data set in history, and determine different evaluation criteria; (ii) Proposing a novel MCDM model that elucidates the intricate interrelationships among various service quality criteria. This model not only evaluates airline performance with precision but also offers a proactive diagnostic tool for airlines to continually refine their service offerings, ensuring a timely and holistic assessment of service quality that enhances both ranking efficiency and stability; (iii) Presenting a visual ranking system, utilizing a directed topological hierarchical graph to illustrate the service quality of 80 global airlines. This innovative representation provides a clear and actionable benchmarking tool for airlines, enabling them to visualize their competitive standing and prioritize areas for service enhancement based on customer feedback.

The target audience of this paper is divided into three categories. The first category comprises researchers in multi-criteria decision making or group consensus aggregation, who can utilize the proposed methodology to perform similar analyses on other large datasets and can explore the integration of old and new techniques. The second category is airline management decision makers, who can use the methodology provided in this study to dynamically benchmark their service quality and identify specific service attributes that resonate with their customers, leading to more targeted and effective service improvements. The third category is that of airline passengers, who can utilize the numerical analysis, ranking results and visualization topology maps obtained from the study to inform their travel choices.

The remainder of this paper is organized as follows. Section 2 provides a review of past research and progress. Section 3 describes the text-mining and MCDM method. Section 4 presents the results of an empirical case study on airline service quality and discusses the outcomes. Section 5 discusses the obtained results and findings. Finally, Section 6 presents the conclusions of this paper. It outlines the limitations of the model and makes recommendations for further research.

2. Literature review

Service quality is defined as a customer's evaluation of a service provider's efficiency and the effectiveness of its offerings (Huang, 2010), as well as the interaction between these aspects and other potential influencing variables (Gursoy et al., 2005). It could also be regarded as the customer's comprehensive appraisal of a service procedure (Chen and Chang, 2005). In the airline industry, service quality is a critical determinant of customer satisfaction (Jiang and Zhang, 2016; Chen and Chang, 2005; Namukasa, 2013). The initial step in creating and delivering high-quality service is an in-depth understanding of individual customer expectations (Zeithaml et al., 1990). However, due to its intangible nature, variability, uniqueness, and the intricacies involved in consumer knowledge and experience, service quality is very difficult to characterize and quantify precisely (Laming and Mason, 2014).

Recent research has identified various subcategories within the criteria for evaluating airline service quality. These include aspects such as pricing (Gourdin, 1988), safety (Gilbert and Wong, 2003), punctuality (Ostrowski et al., 1993), in-flight catering (Elliott and Roach, 1993), baggage handling (Truitt and Haynes, 1994), seating comfort (Bellizzi et al., 2020), pre-boarding services (Bellizzi et al., 2020), in-flight amenities (Bellizzi et al., 2020), and the effectiveness in addressing and resolving complaints (Liou and Tzeng, 2007). Historically, the assessment of service quality in the airline industry has been conducted through a variety of methodologies. For instance, Chen (2008) explored the nexus between airline passengers' satisfaction, perceived value, and service quality via structural equation modeling. Leon and Martín (2020) utilized fuzzy partitioning to The objective of this study was to evaluate the technical and functional quality of the US airline sector in relation to passenger satisfaction. Furthermore, the Kano model was applied to assess quality risks in Taiwanese airlines, with the conclusion that subpar service quality leads to customer dissatisfaction (Hu and Hsiao, 2016).

The SERVQUAL scale represents the most comprehensive and widely employed model for understanding service quality. As cited in Parasuraman et al. (1985), it is a comprehensive model that encompasses five key dimensions: tangibility, reliability, responsiveness, assurance, and empathy. The model encompasses five key areas: tangibility, reliability, responsiveness, assurance, and empathy. These elements collectively enable the effective assessment of clients' perceptions of service quality. The term "tangibility" is used to describe the physical presentation of services, such as in-flight technology and catering standards. Reliability pertains to the airline's credibility, encompassing aircraft safety and crew expertise. The concept of responsiveness encompasses the interaction and communication between the crew (both on the ground and onboard) and passengers. Assurance is indicative of the certainty and confidence provided by the airline's services, including aspects such as the proficiency of the crew in languages other than their native tongue. Finally, empathy pertains to the airline's approach to handling customer complaints and its ability to provide personalized service (Parasuraman et al., 1985, 1988). It is of paramount importance to comprehend the manner in which customer expectations are formed and their perception of service quality, as this is the foundation of the SERVQUAL. A positive quality impression from the customer is only generated when the service provider meets or exceeds these expectations, as demonstrated by Robledo (2001).

In the domain of airline service quality, the integration of text mining techniques with the established SERVQUAL scale has emerged as a robust approach to investigate the subtleties of service quality assessment. Text mining, a methodology that extracts pertinent information from unstructured text data such as online reviews, employs natural language processing, machine learning, and statistical techniques (Jo, 2019). Latent semantic analysis (LSA) is a technique that analyzes the relationships between a set of documents and the terms they contain, producing a set of concepts related to the documents and terms (Muzumdar et al., 2024). The application of Singular Value Decomposition (SVD) enables the reduction of the complexity of the document-term matrix while maintaining the intrinsic similarity structure among the documents and terms, as demonstrated in Wagire et al. (2020). Its applicability extends to information retrieval, document clustering, and topic modeling. Its efficacy has been substantiated in service quality evaluation (Vencovskỳ, 2020; Badanik et al., 2023; Shah et al., 2021). The application of text mining to customer reviews and feedback enables researchers to extract valuable insights and sentiments, providing a more nuanced understanding of customers' perceptions mapped to the structured topics of SERVQUAL (Mejia et al., 2021; Chatterjee et al., 2022). Automated extraction of SERVQUAL topics from online reviews enables comparison across various airlines, regions, and customer demographics (Bogicevic et al., 2017). For example, Tian et al. (2020) employed social media data to assess airline service quality through SERVQUAL indicators. In contrast, Sezgen et al. (2019) analyzed over 5,000 passenger reviews from TripAdvisor, correlating them with the SERVQUAL scale to facilitate customer satisfaction analysis for airline managers. This integration of SERVQUAL and text mining represents a significant advancement in our understanding of airline service quality. It provides a comprehensive and adaptable evaluation framework that aligns with the evolving expectations of passengers in the dynamic aviation sector.

TOPSIS (Hwang and Yoon, 1981; Yoon, 1987) is a comprehensive ranking method based on identifying the optimal solution that is closest to the positive ideal solution and furthest from the negative ideal solutions. This is in accordance with the findings of Chen and Hwang (1992), who proposed that the ideal solution should be chosen based on the minimum geometric distance from the positive ideal solution and the maximum distance from the set of negative ideal solutions. The VIKOR technique is employed to resolve situations of multi-objective decision-making that are characterized by conflicting criteria (Opricovic, 1998; Opricovic and Tzeng, 2004). The process of finding a compromise solution involves ranking and selecting options in the context of the competing criteria (Opricovic and Tzeng, 2004). AISM represents an extension of the ISM method. It breaks down a complex system's constituent parts into smaller parts, arranges those parts in a cause-and-effect hierarchy through a series of Boolean and topological operations, and then identifies the topological structure and hierarchical graph (Li et al., 2023). AISM builds upon the result-oriented hierarchical ranking rules of ISM by introducing a cause-oriented hierarchical ranking. This enables the generation of directed topological diagrams that are in opposition to the ISM ranking rules (Biao and Wei, 2020). The use of AISM to analyze complex systems allows the structure of these systems to be determined without affecting their functionality, and a simple, hierarchical directed topology diagram can be produced.

Our methodology integrates LSA, TOPSIS, VIKOR, and AISM to develop an equitable and comprehensible quality rating system. LSA facilitates data collection, analysis, and subsequent sentiment assessment using a sentiment dictionary. The TOPSIS and VIKOR methods are employed for data reduction and to ascertain average distances to ideal, compromise, and extremal solutions. Additionally, a partial order operation on the data is executed to derive the corresponding relationship matrix. The final result of this process, aided by the AISM approach, is a directed hierarchical topological plot, which effectively constitutes the airline service quality ranking. This ranking is achieved through continuous clip-forcing approximation.

3. Methods

Fig. 1 depicts the complete model development procedure.

Table 1
80 airlines analyzed in our study.

Number	Airline	Number	Airline
A1	Aegean Airlines	A41	IndiGo
A2	Aer Lingus	A42	Japan Airlines
A3	Air Arabia	A43	Jet2 Airlines
A4	Air Astana	A44	JetBlue Airways
A5	Air Canada	A45	Jetstar Airways
A6	Air France	A46	Jetstar Asia
A7	Air New Zealand	A47	KLM Royal Dutch Airlines
A8	Air Transat	A48	Korean Air
A9	AirAsia	A49	Kuwait Airways
A10	airBaltic	A50	LATAM
A11	Alaska Airlines	A51	LOT Polish
A12	American Airlines	A52	Lufthansa
A13	ANA All Nippon Airways	A53	Malaysia Airlines
A14	Asiana Airlines	A54	Oman Air
A15	Austrian Airlines	A55	Peach
A16	Azerbaijan Airlines	A56	Philippine Airlines
A17	Azul Airlines	A57	Qantas Airways
A18	Bangkok Airways	A58	Qatar Airways
A19	British Airways	A59	Rex Airlines
A20	Brussels Airlines	A60	Royal Air Maroc
A21	Cathay Pacific Airways	A61	Royal Brunei Airlines
A22	China Airlines	A62	Ryanair
A23	China Southern Airlines	A63	SAS Scandinavian
A24	Delta Air Lines	A64	Saudi Arabian Airlines
A25	EasyJet	A65	Scoot
A26	Emirates	A66	Singapore Airlines
A27	Ethiopian Airlines	A67	South African Airways
A28	Etihad Airways	A68	Southwest Airlines
A29	Eurowings	A69	SunExpress
A30	EVA Air	A70	Swiss International Air Lines
A31	Fiji Airways	A71	TAP Portugal
A32	Finnair	A72	Thai Airways
A33	flyDubai	A73	Turkish Airlines
A34	Flynas	A74	United Airlines
A35	Garuda Indonesia	A75	Vietnam Airlines
A36	Gulf Air	A76	Virgin Atlantic
A37	Hainan Airlines	A77	Virgin Australia
A38	Hawaiian Airlines	A78	Vistara
A39	Hong Kong Airlines	A79	Vueling Airlines
A40	Iberia	A80	WestJet

3.1. Data collection and cleaning

Airline service rankings have long been of interest to researchers and industry analysts alike. In order to gain a comprehensive understanding of the industry, we selected 80 airlines for analysis. The details of these airlines are presented in Table 1.

A comprehensive collection of online reviews for 80 airlines was undertaken, sourced from various travel websites in multiple languages. These included TripAdvisor (tripadvisor.com), Skytrax (skytraxratings.com), Trip (trip.com), and Qunar (qunar.com). In addition, prominent social media platforms were consulted, including X (x.com), Facebook (facebook.com), Weibo (weibo.com), and Xiaohongshu (xiaohongshu.com). The reviews encompassed a diverse range of service aspects, including but not limited to flight experience, staff behavior, food quality, and seat comfort. A minimum of 200 reviews were gathered for each airline, amassing a substantial dataset of 61,087 reviews. The data collection strategy was meticulously designed to amass a robust and representative dataset, reflecting the breadth of customer opinions and preferences concerning airline service quality. In order to extract the reviews from the websites, we employed web scraping tools, such as BeautifulSoup (Richardson, 2007) in Python and Selenium. Additionally, we utilized the Google Translate API (translate.google.com) to translate the reviews from various languages, including Chinese, French, Spanish, Arabic, and etc., into English.

In the subsequent phase, we undertook the preprocessing of text data, with the objective of eliminating noise and superfluous elements such as punctuation, stopwords, numbers, URLs, and more. This process

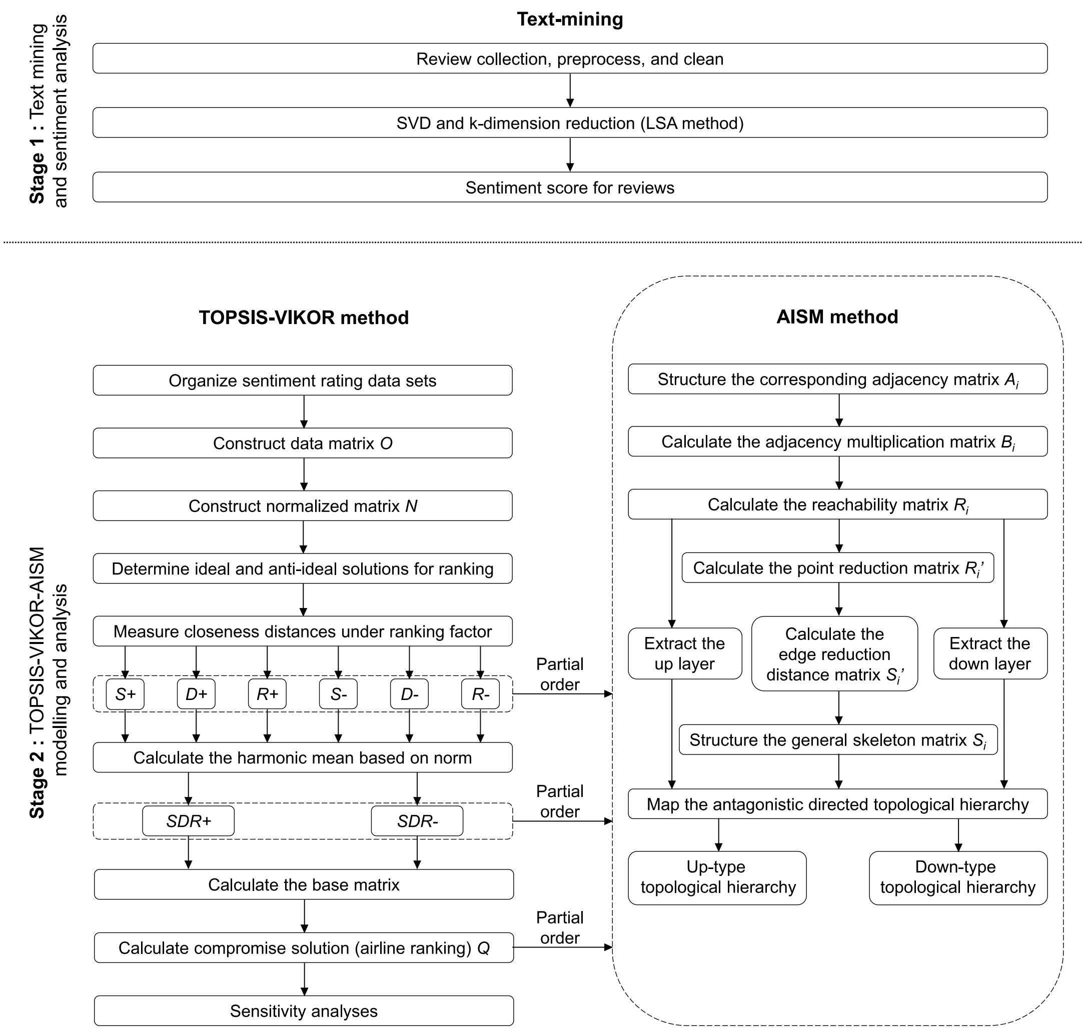

Fig. 1. Diagram of the text-mining method and TOPSIS-VIKOR-AISM model process.

also involved the application of stemming and lemmatization techniques, which streamline words to their base forms and harmonize the vocabulary. The overarching goal of this data cleaning procedure was to enhance the textual data's quality and coherence, while simultaneously reducing the dimensionality of the term-document matrix. For this task, we employed the NLTK package (Loper and Bird, 2002) in Python. Furthermore, we conducted meticulous manual reviews to identify and rectify any spelling and grammatical inaccuracies within the reviews, thereby ensuring the veracity and precision of the text data.

To illustrate the efficacy of our data cleaning process, we present exemplars of both the original and cleaned reviews in Table 2 As illustrated, the data cleaning operation effectively expunged extraneous symbols and words, as well as streamlined sentences. This crucial step substantially augmented the efficiency of the subsequent analytical processes.

3.2. Identification and quantification of evaluation indicators

Employing the framework of the five SERVQUAL topics and incorporating additional research and practical insights, we devised fifteen service quality assessment criteria across five categories, as delineated in Table 3.

The objective of our text-mining endeavor was to discern pivotal themes and affective responses from customer feedback and to quantify these through numerical assessments. To this end, we employed the Latent Semantic Analysis (LSA) technique, which enabled us to extract salient topics and sentiments from the amassed reviews. LSA, a method employing Singular Value Decomposition (SVD), serves to reduce the dimensionality of a term-document matrix, thereby unveiling the underlying semantic structure of the text. This analysis comprises three primary stages. The initial step involves representing documents and terms within a vector space, creating a term-document matrix that captures the concurrent occurrence of terms within documents. This matrix is then subject to term frequency-inverse document frequency (tf-idf) weighting, which accentuates terms that are distinctive in describing the document's content. The final stage involves SVD, which decomposes the term-document matrix, denoted as $X_{t\times d}$, into three matrices: $T_{t\times m}$ (a column-orthogonal matrix with topics represented by m), $S_{m\times m}$ (a diagonal matrix containing singular values in descending order), and $D_{d\times m}$ (a transposed column-orthogonal matrix). Here, t and d represent the number of terms and documents, respectively. These matrices are truncated to a chosen number of topics, k, to filter out noise and distill latent semantic linkages within the text corpus. The decomposition and truncation process is depicted in Fig. 2.

In constructing the term-document matrix from the curated reviews, each row corresponded to a word, and each column to a review. We employed the Scikit-learn package (Kramer and Kramer, 2016) in Python for the LSA procedure, selecting the top 'k' topics based on singular values and deriving the pertinent topic keywords and scores for each review.

For sentiment analysis, we utilized a scoring dictionary that allocated a value to words based on their polarity and intensity. The

Table 2
Examples of the original reviews and the cleaned reviews.

Number	Original Review	Cleaned Review
1	I flew with Airline A from London to New York and I had a great experience. The arrival service were helpful, the food was delicious, and the seat was comfortable. I would definitely fly with them again.	fly Airline A London New York great experience arrival service helpful food delicious seat comfortable definitely fly again
2	Airline B is the worst airline ever. They canceled my flight without any notice and refused to refund me. They have no customer service and no respect for their passengers. I will never use them again.	Airline B worst airline ever cancel flight without notice refuse refund no customer service no respect passenger never use
3	Airline C has excellent service and value for money. The flights are always on time and the cabin crew are very professional and courteous. The entertainment system is also very good and has a lot of options. I highly recommend Airline C! :)	Airline C excellent service value money flights on time cabin crew very professional courteous entertainment system very good lot option highly recommend Airline C

Table 3
Criteria are selected in the study.

Topic	Indicator	Evaluation Indicators
Tangibility	C_1	Seat comfort
	C_2	Quality of meals
	C_3	In-flight entertainment
Reliability	C_4	Staff professionalism
	C_5	Aircraft punctuality
	C_6	Aircraft safety
Responsiveness	C_7	Staff attitudes
	C_8	Service attentiveness/efficiency
	C_9	Problem-solving skills
Assurance	C_{10}	Staff skills
	C_{11}	Staff grooming
	C_{12}	Service fairness
Empathy	C_{13}	Vulnerable group services
	C_{14}	Pre-boarding procedures
	C_{15}	Transfer and arrival services

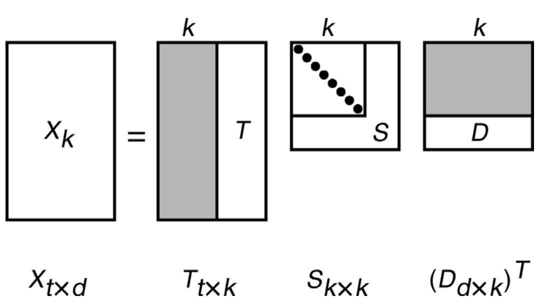

Fig. 2. The process of decomposition and truncation.
Source: adopted from Berry et al. (1995)

SentiWordNet 3.0 dictionary (Baccianella et al., 2010), a lexical resource tailored for opinion mining, was employed. It assigns objective scores to each synset (a set of synonyms) in WordNet. Words in the reviews were aligned with synsets in the dictionary to obtain word-specific sentiment scores. We then averaged these scores for each review, calculating an aggregate sentiment score. Additionally, the TextBlob package (Loria et al., 2018) in Python facilitated sentiment analysis, assigning a polarity score from 0 (negative) to 5 (positive) to each review. Table 4 elucidates the correlation between sample emotion words and their respective scores.

A review's score, situated between two sentiment thresholds, indicates the presence of both positive and negative elements or words with varying intensity levels. For instance, a score of 4.3, hovering between 4 and 5, suggests a predominantly positive review but not exceedingly so. Such a review might feature highly positive words like "excellent" or "amazing", coupled with moderately positive terms like "good" or "nice". Alternatively, it might include positive words alongside neutral or marginally negative terms, such as "okay" or "average".

Table 4
Basic correspondence between each sample emotion word and emotion score.

Emotion word	Score
excellent/amazing/wonderful	5
good/nice/happy	4
fair/okay/pleasant	3
average/neutral/indifferent	2
bad/awful/terrible	1
worst/horrible/disgusting	0

To exemplify our text-mining methodology, Table 5 presents sample extracts from the reviews. As shown in the table, the reviews were labeled according to the five SERVQUAL topics and broken down into specific sub-indicators. Sentiments are classified as positive, negative, or neutral, based on their polarity scores. For example, the review "Airline A has excellent service and value for money" received a sentiment score of 3.75, indicative of a positive sentiment.

We created an original evaluation matrix O based on m evaluation objects and n evaluation indicators, where x_{ij} is the average score of each evaluation object in the evaluation indicator. An example is presented in Table 6.

In this matrix, n and m are the number of airlines and indicators, respectively. Thus,

$$O = x_{ij}, \quad i = 1, \ldots, n; \quad j = 1, \ldots, m. \tag{1}$$

3.3. Construction of TOPSIS-VIKOR-AISM model

To produce N, the initial evaluation matrix O is normalized as follows:

$$N = r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \quad i = 1, \ldots, n, j = 1, \ldots, m. \tag{2}$$

We normalize the compiled data on airline service quality and arrange it into a raw matrix covering the different airlines, indications, and scores. We compute utility values S^+, S^-, Euclidean distances D^+, D^-, and regret values R^+, R^- using the TOPSIS and VIKOR. We then compute the mean of the distances to positive and negative ideal points, SDR^+ and SDR^-, from the compromise solution Q. Three sets of adversarial hierarchical topologies are successively computed for the topologies acquired using the AISM approach, as depicted on the right

Table 5
Examples of topics and sentiments extracted from the reviews.

Number	Review	Topic	Indicator	Indicator Score	Sentiment	Polarity Score
1	Airline A has excellent service and value for money	Assurance	Staff skills	4	Positive	4.5
2	Airline B is the worst airline ever. They canceled my flight without any notice and refused to refund me	Reliability	Aircraft punctuality	0.5	Negative	1
3	Airline C has a very good entertainment system and a lot of options	Tangibles	In-flight entertainment	4	Positive	4
4	I flew with Airline A from London to New York and I had a great experience. The arrival service were helpful	Empathy	Transfer and arrival services	4.5	Positive	4
5	Airline B has no customer service and no respect for their passengers	Responsiveness	Staff attitudes	1	Negative	1.5
6	Airline C's seat was uncomfortable and the food was terrible	Tangibles	Seat comfort	1.5	Negative	1

Table 6
Original assessment matrix.

Airline	C_1	C_2	⋯	C_m
A_1	x_{11}	x_{12}	⋯	x_{1m}
A_2	x_{21}	x_{22}	⋯	x_{2m}
⋯		⋯		
A_n	x_{n1}	x_{n2}	⋯	x_{nm}

side of Fig. 1. An intuitive hierarchical link between airline service quality and S^+, S^-, D^+, D^-, R^+, R^-, SDR^+, SDR^-, and Q is obtained.

Step 1: Calculate the positive and negative ideal solutions F_j^+ and F_j^-.

$$F_j^+ = [t_1^+, \dots, t_j^+, \dots, t_m^+] = [\max(t_{11}, t_{21}, \dots, t_{n1}), \dots, \max(t_{1j}, t_{2j}, \dots, t_{nj}), \dots, \max(t_{1m}, t_{2m}, \dots, t_{nm})]; \tag{3}$$

$$F_j^- = [t_1^-, \dots, t_j^-, \dots, t_m^-] = [\min(t_{11}, t_{21}, \dots, t_{n1}), \dots, \min(t_{1j}, t_{2j}, \dots, t_{nj}), \dots, \min(t_{1m}, t_{2m}, \dots, t_{nm})]. \tag{4}$$

Step 2: Calculate the alternative solution and compute the positive and negative ideal solution distances D^+ and D^-.

$$D^+ = \sqrt{\sum_{j=1}^{m} (t_{ij} - t_j^+)^2}, \quad i = 1, \dots, n; \tag{5}$$

$$D^- = \sqrt{\sum_{j=1}^{m} (t_{ij} - t_j^-)^2}, \quad i = 1, \dots, n. \tag{6}$$

Step 3: Determine the best and worst evaluation functions f_j^+ and f_j^-.

$$f_j^+ = \max_i t_{ij}, \quad i = 1, \dots, n, j = 1, \dots, m; \tag{7}$$

$$f_j^- = \min_i t_{ij}, \quad i = 1, \dots, n, j = 1, \dots, m. \tag{8}$$

Step 4: Calculate the weighted normalized Manhattan distance S_i and the weighted normalized Chebyshev distance R_i.

$$S_i = \sqrt{\sum_{j=1}^{m} w_j \frac{f_j^+ - f_{ij}}{f_j^+ - f_j^-}}, \quad i = 1, \dots, n, j = 1, \dots, m; \tag{9}$$

$$R_i = \max_j [\frac{w_j (f_j^+ - f_{ij})}{(f_j^+ - f_j^-)}], \quad i = 1, \dots, n, j = 1, \dots, m, \tag{10}$$

where, w_j is the weight of each indicator, indicating its relative importance.

Step 5: Calculate the compromise solution. If we suppose the following Eq. (11) holds.

$$S^- = \min_i S_i; \ S^+ = \max_i S_i; \ R^- = \min_i R_i; \ R^+ = \max_i R_i. \tag{11}$$

Then we define that SDR^+ and SDR^- are the harmonic means of the distances of each element to the positive and negative ideal points respectively. So the compromise solution Q_i can be determined as follows using Eq. (12).

$$Q_i = (1-k)\left(\frac{SDR_i^+ - \min\left(SDR_i^+\right)}{\max\left(SDR_i^+\right) - \min\left(SDR_i^+\right)}\right) + k\left(\frac{\max\left(SDR_i^-\right) - SDR_i^-}{\max\left(SDR_i^-\right) - \min\left(SDR_i^-\right)}\right). \tag{12}$$

The allocation coefficient k is typically set to 0.5, representing the weight of the maximum group utility strategy being adopted.

Step 6: Build the adjacency relationship matrix. The partial order relationship operation transfers the evaluation matrix on the left to the relationship matrix on the right based on the partial order rules. These are the guidelines for partial orders. For an evaluation matrix D containing m columns, all columns, i.e., the indicator dimensions, have the same properties and are thus comparable. To compare the advantages and disadvantages of dimensions, we must determine whether the indicators are positive or negative. When larger values are better and smaller values are worse, the indicator is said to be positive. Such indicators are denoted as $p_1, p_2, \dots, p_m$. When larger values are worse and smaller values are preferable, the indicator is said to be negative, denoted as $q_1, q_2, \dots, q_m$. For any two rows x, y in D, if the indicators are positive, we have

$$d_{(x,p_1)} \geq d_{(y,p_1)}, d_{(x,p_2)} \geq d_{(y,p_2)}, \dots, \ d_{(x,p_m)} \geq d_{(y,p_m)}. \tag{13}$$

The partial order connection between x and y is noted as $x \prec y$, which suggests that y is superior to x if the aforementioned rule is satisfied. The internal relationship between the influencing factors can then be discovered by expert scoring in accordance with the various evaluation indices. The element a_{ij} in the adjacency matrix A can then be written as

$$a_{ij} = \left\{ \begin{array}{ll} 0, & x \prec y; \\ 1, & \text{No perfect relationship between } x \text{ and } y. \end{array} \right\} \tag{14}$$

Step 7: The accessibility matrix reflects the lengths of the paths connecting any two nodes in a directed connected network. It is necessary to first compute the multiplicative adjacency matrix B for any given basic matrix.

$$B = A + I, \tag{15}$$

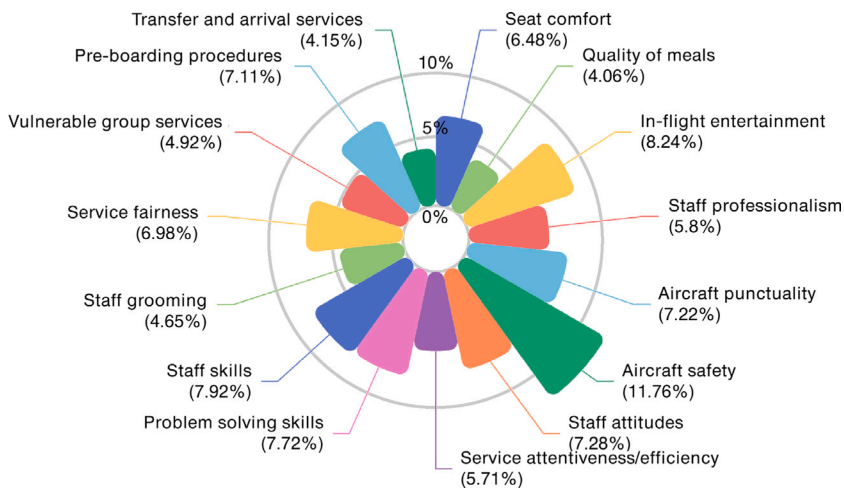

Fig. 3. The quantity distribution of each indicator.

where B is the multiplicative adjacency matrix and I is the unit matrix. The concatenation of B results in the reachable matrix R.

$$B^{k-1} \neq B^k = B^{k+1} = R. \tag{16}$$

The cycle in the reachable matrix R is treated as a point in the point reduction operation on the reachable matrix R, from which a new reachable matrix R' can be generated. The edge reduction technique is applied to R' to obtain the skeleton matrix S', which essentially eliminates redundant routes.

$$S' = R' - \left(R' - I\right)^2 - I. \tag{17}$$

The general skeleton matrix S can be obtained if the cyclic loops in S' are modeled as minimum daisy chains.

Step 8: Extraction of the hierarchy. For any accessibility matrix, there exist a reachable set R, a prior set Q, and a common set T, where $T = R \cap Q$. Consider a relational matrix A as an illustration. For each element e_i in A, there are two possible scenarios.

- All elements whose corresponding row value is 1 constitute the reachable set, and $R = (e_i)$;
- The entire set of elements with a column value of 1 constitutes the prior set $Q(e_i)$. The common set of the reachable set $R = (e_i) \cap Q(e_i)$ and the prior set is called $T(e_i)$.

The layer extraction method is as follows.

- Extraction of the topology of up-type structures. The term 'result-first hierarchical extraction' refers to up-type structures, which follow the rule $T(e_i) = R(e_i)$. The main idea is to take the system components that make up the end result, place them in the top level, and then extract them via analogy;
- Topology extraction of the down-type structures. We consider this to be a cause-based hierarchical extraction technique for structures which follow the rule $T(e_i) = Q(e_i)$. The fundamental idea is that the system components that are the root causes are first isolated and positioned at the bottom of the hierarchy, after which they are extracted via analogy.

4. Results

Following text mining, the distribution of the number of all online reviews mapped to each indicator can be found in Fig. 3. Notably, 'aircraft safety' emerges as the predominant keyword, constituting 11.78% of the mentions. Other significant keywords include 'in-flight entertainment' (8.24%) and 'staff skills' (7.92%), highlighting focal areas of passenger concern.

Table 7
Top 20 most frequent keywords during text mining.

Keyword	Number	SERVQUAL Topic
flight	22,340	Reliability
service	20,980	Assurance
staff	19,872	Empathy
seat	18,761	Tangibles
food	17,655	Tangibles
time	16,544	Reliability
entertainment	15,435	Tangibles
customer	14,329	Responsiveness
experience	13,211	Assurance
value	12,100	Assurance
refund	11,992	Responsiveness
delay	11,881	Reliability
comfort	11,777	Tangibles
friendly	11,663	Empathy
helpful	11,632	Empathy
cancel	11,440	Reliability
respect	11,339	Responsiveness
professional	11,221	Assurance
option	11,110	Tangibles
money	9,927	Assurance

The process of text mining has elucidated the top 20 keywords recurrent in customer feedback, as tabulated in Table 7. This table offers insightful patterns regarding customer perceptions and preferences in airline service quality. For instance, 'flight' surfaces as the most frequently cited keyword, with 22,340 occurrences, predominantly under the 'reliability' theme. This underscores a prevalent customer focus on flight performance aspects such as punctuality and safety. Similarly, the keyword 'service', appearing 20,980 times and classified under the 'assurance' theme, reflects the high value passengers place on aspects like staff proficiency and presentation, often manifesting in either commendations or criticisms of service quality.

Sentiment analysis yields the service satisfaction scores across five SERVQUAL thematic areas for 80 airlines, as detailed in Table 8.

Equations ((5), (6), (11)) facilitate the calculation of positive and negative utility values (S^+, S^-), ideal solutions (D^+, D^-), and regret values (R^+, R^-). The harmonic mean distances from each element to the positive and negative ideal points, alongside the compromise solution (Q_i), are computed via Eq. (12). These findings are enumerated in Table 9, with the far-right column presenting the rankings based on Q_i.

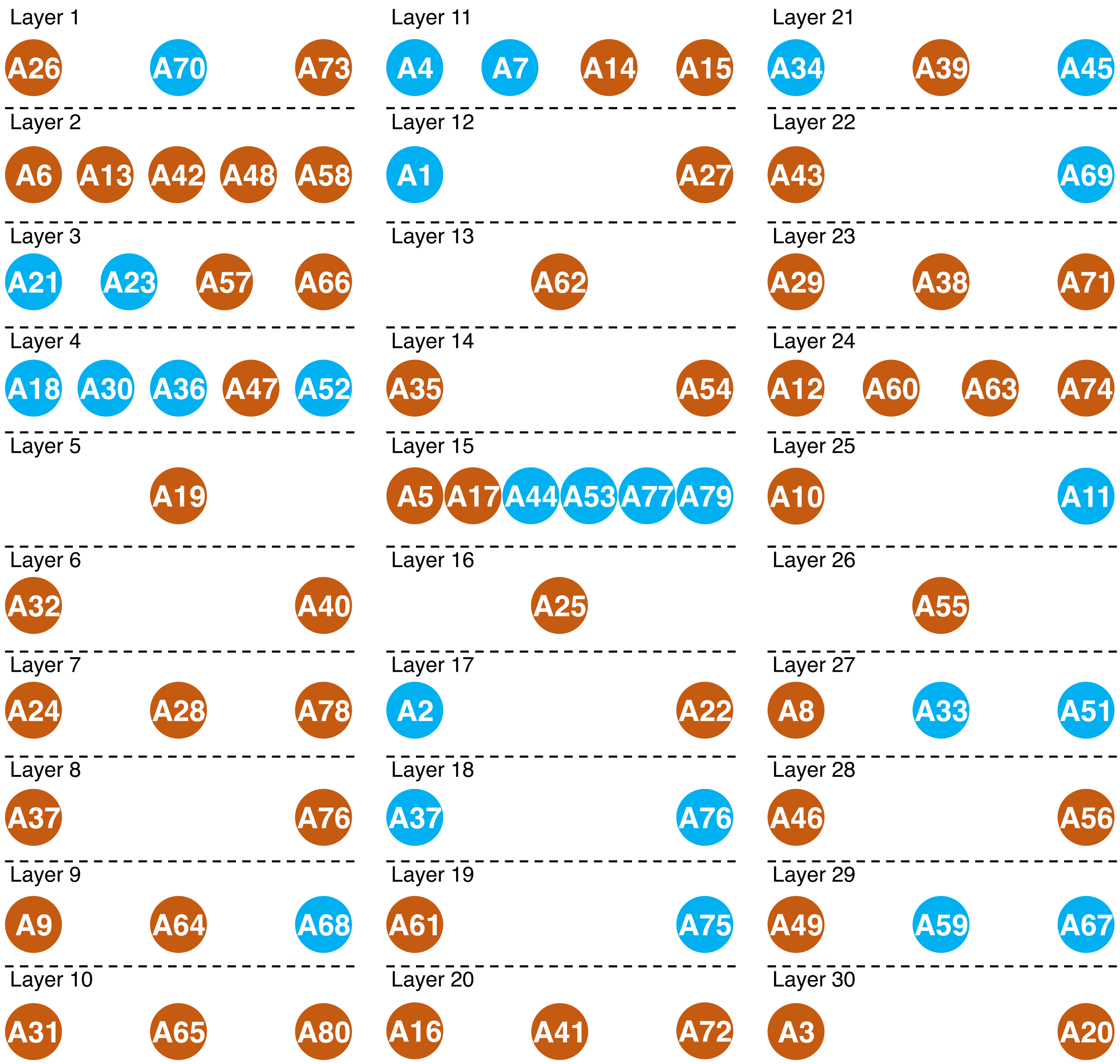

Fig. 4. Up-type directed topological hierarchy diagrams.

The combination of data for D^+, D^-, S^+, S^-, R^+, R^-, and subsequent pinch-force computations yields topological hierarchy diagrams, as depicted in Figs. 4 and 5. In these diagrams, brown circles symbolize airlines with stable rankings, while blue circles indicate those susceptible to fluctuating ratings. Figs. 4 and 5 present the topological hierarchy of 80 airlines, showcasing their relative positions and the stability of their rankings within the industry. The figures are organized into multiple layers, reflecting the comprehensive AISM analysis. Each layer represents a distinct level of service quality among the airlines, with the first layer indicating the highest echelon of service. This analysis is not merely a ranking of airlines' service quality; it segments them into 30 distinct layers, wherein airlines may share rankings. For example, Emirates (A26) and Turkish Airlines (A73), situated in the first layer, display comparable competencies in Tangibility and Empathy, albeit with minor differences in Reliability and Responsiveness Assurance. The hierarchy depicted in Figs. 4 and 5 provides insights into the competitive dynamics among the airlines and inform the final rankings, offering a visual representation of the airlines' standings and their potential movement within the industry's service quality layers. The final ranking, adhering to these principles, is exhibited in Table 10. Airlines situated in the same topological layer (brown circles) may be considered to have comparable levels of service quality, and their rankings are reflected in Table 10, for example, using the "=1" ranking. In the event that an airline does not belong to the same layer (blue circles) in the UP-type and DOWN-type directed topological hierarchical maps, its ranking will be compared with that of other airlines in accordance with the following rules: (i) In the event that an airline's change occurs in two different layers, it will be ranked only lower than its first layer and higher than the second. To illustrate, Swiss International Air Lines (A70), which is in layer 1 in UP-type and layer 2 in DOWN-type, is ranked 3, below Emirates (A26) and Turkish Airlines (A73), which are both in layer 1, and below Air France (A6), ANA (A13), Air France (A6), ANA (A13), Japan Airlines (A42), Korean Air (A48) and Qatar Airways (A58). Another illustrative example is Aer Lingus (A2), which is situated in the layer 17 in the UP-type and in the layer 19 in the DOWN-type. It is noteworthy that this airline is only below China Airlines (A22), which is also situated in the layer 17, and is higher than Vietnam Airlines (A75), which is situated in the layer 18. (ii) In the event that an airline is situated in two different layers with respect to another airline, but across fewer layers, the former is ranked higher. To illustrate, if Air New Zealand (A7) is situated in layers 11–12, while Air Astana (A4) is situated in layers 11–13, then Air New Zealand (A7) is ranked higher than Air Astana (A4).

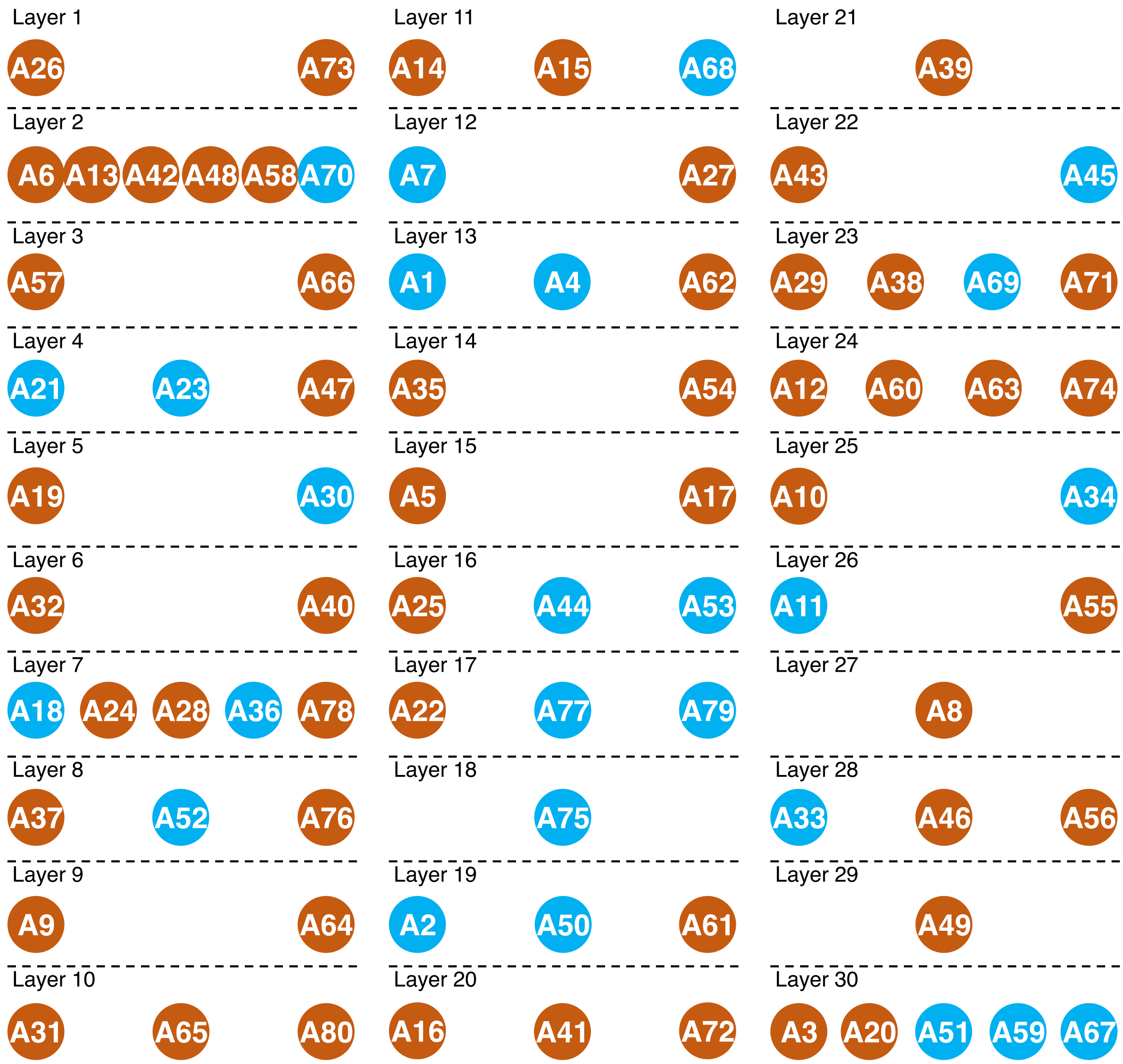

Fig. 5. Down-type directed topological hierarchy diagrams.

5. Discussion

5.1. Sensitivity analysis

In order to assess the robustness of the proposed integrated approach, a sensitivity analysis has been performed. As shown in Eq. (12), the value of the allocation coefficient k may have an impact on how a and b are allocated. Adjusting k would result in different service quality scores for each airline, thus affecting its ranking. The value of k was varied from 0 to 1 in increments of 0.0001, resulting in a ranked set of 10,000 rankings with different assignment coefficients. Two ranking correlation coefficients were calculated, Spearman's ρ and Kendall's τ, respectively, to measure the correlation between the different ranking sets. Furthermore, the Kruskal–Wallis test, a non-parametric method, was employed to ascertain whether statistically significant differences existed between the multiple sets of rankings. The results of all calculations are presented in Table 11.

As demonstrated in Table 11, the Spearman's ρ value of 0.998 indicates a robust positive correlation between this set of ranked sets, thereby substantiating the stability of the ranking outcomes. The Kendall's τ value of 0.997 suggests that the correlation between the ranked sets is exceptionally strong, and the ranking results can be regarded as highly reliable. Furthermore, the p-value of the H-statistic is 0.94, as determined by the Kruskal–Wallis test. This indicates that there is no statistically significant difference between the multiple ranking. These results demonstrate that the proposed methodology produces results with a high degree of reliability, which facilitates decision-making in this situation.

5.2. Discussion of the results

In our research, we employed text mining and Multi-Criteria Decision Making (MCDM) techniques to analyze online reviews of 80 airlines, uncovering intriguing patterns and insights into customer perceptions and preferences regarding airline service quality. Our proposed methodology facilitates a multi-dimensional satisfaction assessment, demonstrating that more effective and realistic evaluations and analyses are achievable. The case study findings indicate that passengers place significant emphasis on various aspects of service quality, including aircraft safety, service provision, and staff conduct. These elements are frequently the subject of passenger satisfaction or dissatisfaction. The review of online feedback revealed that commonly

Table 8
Service satisfaction scores across five thematic topics for 80 airlines.

Number	Airline	Tangibility	Reliability	Responsiveness	Assurance	Empathy
A1	Aegean Airlines	0.164	0.437	0.354	0.402	0.230
A2	Aer Lingus	−0.393	−0.609	−0.524	−0.071	−0.918
A3	Air Arabia	−1.963	−1.909	−1.874	−1.489	−1.897
A4	Air Astana	0.315	0.251	0.422	0.537	−0.142
A5	Air Canada	−0.596	−0.559	−0.085	−0.088	−0.209
A6	Air France	1.666	1.500	1.670	1.870	1.327
A7	Air New Zealand	0.450	0.572	0.320	0.064	0.297
A8	Air Transat	−1.524	−1.808	−1.654	−1.641	−1.407
A9	AirAsia	0.940	0.893	0.455	0.098	0.415
A10	airBaltic	−1.052	−1.200	−1.536	−0.999	−1.323
A11	Alaska Airlines	−1.440	−0.964	−1.148	−1.472	−0.884
A12	American Airlines	−1.035	−1.166	−1.114	−1.219	−1.542
A13	ANA All Nippon Airways	1.328	1.551	1.805	1.786	1.647
A14	Asiana Airlines	0.484	0.758	0.033	0.790	0.365
A15	Austrian Airlines	0.619	0.977	0.371	0.132	0.196
A16	Azerbaijan Airlines	−0.697	−0.424	−0.625	−0.577	−0.631
A17	Azul Airlines	−0.242	−0.305	−0.473	−0.341	−0.158
A18	Bangkok Airways	1.024	0.842	0.793	0.891	1.361
A19	British Airways	1.227	1.433	1.029	1.195	1.462
A20	Brussels Airlines	−1.929	−1.791	−1.722	−1.590	−1.610
A21	Cathay Pacific Airways	1.547	0.640	1.350	1.516	1.006
A22	China Airlines	−0.157	−0.491	−0.405	−0.358	−0.277
A23	China Southern Airlines	0.957	0.876	1.316	1.482	1.479
A24	Delta Air Lines	1.362	0.893	1.384	1.060	1.006
A25	EasyJet	−0.005	−0.626	−0.557	−0.155	−0.175
A26	Emirates	1.834	1.450	1.654	1.718	1.799
A27	Ethiopian Airlines	0.518	0.251	0.658	0.655	−0.108
A28	Etihad Airways	1.244	0.927	0.708	1.195	1.192
A29	Eurowings	−0.748	−1.048	−0.962	−1.354	−1.306
A30	EVA Air	1.142	0.876	1.080	1.330	1.310
A31	Fiji Airways	0.197	0.268	0.438	0.587	0.702
A32	Finnair	1.277	1.298	1.063	0.908	1.040
A33	flyDubai	−1.491	−1.689	−1.891	−1.978	−1.424
A34	Flynas	−0.714	−0.829	−1.030	−0.898	−1.036
A35	Garuda Indonesia	0.113	0.116	−0.135	0.334	0.534
A36	Gulf Air	0.889	0.977	1.097	0.705	1.209
A37	Hainan Airlines	0.957	1.146	0.405	0.857	1.344
A38	Hawaiian Airlines	−1.423	−1.048	−0.760	−0.780	−1.104
A39	Hong Kong Airlines	−1.204	−1.183	−0.811	−1.016	−0.445
A40	Iberia	0.974	1.180	1.046	1.397	1.158
A41	IndiGo	−0.444	−0.474	−0.591	−0.493	−0.834
A42	Japan Airlines	1.362	1.754	1.789	1.836	1.512
A43	Jet2.com	−0.748	−1.116	−1.081	−1.084	−0.952
A44	JetBlue Airways	−0.444	−0.305	0.016	−0.543	0.280
A45	Jetstar Airways	−1.474	−0.643	−0.962	−0.797	−0.884
A46	Jetstar Asia	−1.406	−1.824	−1.621	−1.657	−1.644
A47	KLM Royal Dutch Airlines	1.311	1.365	1.350	1.094	1.377
A48	Korean Air	1.733	1.686	1.704	1.634	1.664
A49	Kuwait Airways	−1.558	−1.656	−1.924	−1.691	−1.812
A50	LATAM	−0.765	−0.137	−0.220	−0.662	−0.496
A51	LOT Polish	−1.507	−1.723	−1.553	−1.742	−1.492
A52	Lufthansa	0.569	0.471	0.945	1.246	1.361
A53	Malaysia Airlines	−0.039	−0.694	−0.169	−0.358	−0.361
A54	Oman Air	0.197	0.319	0.438	−0.138	0.196
A55	Peach	−1.372	−1.116	−1.097	−1.320	−1.222
A56	Philippine Airlines	−1.659	−1.757	−1.401	−1.776	−1.829
A57	Qantas Airways	1.277	1.889	1.637	1.499	1.462
A58	Qatar Airways	1.834	1.551	1.502	1.397	1.766
A59	Rex Airlines	−1.541	−1.588	−1.486	−1.961	−1.812
A60	Royal Air Maroc	−1.355	−0.711	−1.030	−0.965	−1.475
A61	Royal Brunei Airlines	−0.444	−0.204	−0.709	−0.645	−0.378
A62	Ryanair	0.332	0.201	0.675	0.267	0.264
A63	SAS Scandinavian	−0.917	−1.386	−1.283	−1.100	−0.817
A64	Saudi Arabian Airlines	0.315	0.657	0.675	0.351	0.314
A65	Scoot	0.332	0.977	0.742	0.520	0.230
A66	Singapore Airlines	1.784	1.770	1.451	1.414	1.563
A67	South African Airways	−1.609	−1.639	−1.654	−1.911	−2.015
A68	Southwest Airlines	0.636	0.927	0.540	0.655	0.415
A69	SunExpress	−1.339	−0.997	−1.081	−0.712	−0.715
A70	Swiss International Air Lines	1.581	1.551	1.485	1.718	1.512
A71	TAP Portugal	−0.967	−1.200	−1.266	−1.134	−1.053
A72	Thai Airways	−0.478	−0.457	−0.220	−0.780	−0.580
A73	Turkish Airlines	1.547	1.855	1.890	1.752	1.715
A74	United Airlines	−1.288	−1.369	−1.300	−0.847	−1.171
A75	Vietnam Airlines	−0.528	−0.592	−0.287	−0.172	−0.564
A76	Virgin Atlantic	1.193	1.129	1.654	0.621	0.804
A77	Virgin Australia	−0.140	−0.052	−0.557	−0.678	−0.445
A78	Vistara	0.923	1.298	0.894	0.807	1.107
A79	Vueling Airlines	−0.056	−0.491	−0.591	0.216	0.112
A80	WestJet	0.535	0.268	0.557	0.655	0.415
Average		3.064	3.061	3.059	3.062	3.066

occurring terms, such as ‘flight’, ‘service’, ‘staff’, ‘seat’, ‘food’ and ‘time’, suggest that airlines and stakeholders should intensify their focus on these service quality facets to enhance passenger satisfaction (Park et al., 2020).

The proposed method allows for the comparative ranking of service quality between any two airlines to be determined through the construction of a series of directed topological hierarchical graphs, as illustrated in Figs. 4 and 5. This framework is characterized by a rigid structure. In these graphs, an element is designated as active if it occupies a distinct topological level. Systems comprising active elements are designated as extensionally variable systems, in contrast to topologically rigid systems that lack such elements. The inherent stability and robustness of relationships and order within a topologically rigid system are notable characteristics. The rankings generated

Table 9
Airline distances D^{+}, D^{-} from positive and negative ideal solutions; positive and negative utility values S^{+}, S^{-}; positive and negative regret values R^{+}, R^{-}; harmonic mean SDR^{+}, SDR^{-}; airline ranking with corresponding a_i, b_i, Q_i.

Number	Airline	D^{+}	D^{-}	S^{+}	S^{-}	R^{+}	R^{-}	SDR^{+}	SDR^{-}	a	b	Q_i	Ranking
A73	Turkish Airlines	1.80	24.66	4.71	95.29	0.97	6.96	2.49	42.30	0.00	0.00	0.00	1
A26	Emirates	2.15	24.31	6.17	93.83	1.21	7.17	3.18	41.77	0.02	0.01	0.02	2
A48	Korean Air	2.20	24.21	6.44	93.55	1.10	6.91	3.25	41.56	0.02	0.02	0.02	3
A42	Japan Airlines	2.66	24.03	7.28	92.72	1.59	6.98	3.84	41.24	0.03	0.03	0.03	4
A13	ANA All Nippon Airways	2.74	23.87	7.92	92.08	1.44	6.98	4.03	40.98	0.04	0.03	0.04	5
A58	Qatar Airways	2.81	23.80	8.22	91.78	1.51	7.05	4.18	40.88	0.04	0.04	0.04	6
A6	Air France	2.66	23.71	8.40	91.60	1.41	7.07	4.16	40.80	0.04	0.04	0.04	7
A66	Singapore Airlines	2.87	23.62	8.74	91.25	1.23	6.91	4.28	40.59	0.05	0.04	0.04	8
A70	Swiss International Air Lines	3.15	23.59	9.18	90.82	1.85	7.26	4.73	40.56	0.06	0.04	0.05	9
A57	Qantas Airways	3.13	23.50	9.54	90.46	1.44	6.98	4.70	40.31	0.06	0.05	0.05	10
A47	KLM Royal Dutch Airlines	4.47	21.81	15.99	84.01	2.08	6.51	7.51	37.44	0.13	0.12	0.12	11
A19	British Airways	4.92	21.63	16.82	83.18	2.11	6.50	7.95	37.10	0.14	0.13	0.13	12
A23	China Southern Airlines	5.39	21.52	17.77	82.23	2.59	6.98	8.58	36.91	0.15	0.14	0.14	13
A21	Cathay Pacific Airways	5.61	21.34	18.29	81.71	2.57	6.98	8.82	36.68	0.16	0.14	0.15	14
A30	EVA Air	5.69	20.78	20.03	79.97	2.42	6.51	9.38	35.75	0.17	0.17	0.17	15
A40	Iberia	5.97	20.89	19.93	80.06	2.74	6.32	9.55	35.76	0.18	0.17	0.17	16
A24	Delta Air Lines	5.87	20.77	20.21	79.79	2.66	6.09	9.58	35.55	0.18	0.17	0.17	17
A32	Finnair	6.02	20.64	20.76	79.24	2.73	6.38	9.84	35.42	0.19	0.17	0.18	18
A76	Virgin Atlantic	6.48	20.32	21.95	78.04	2.83	6.05	10.42	34.81	0.20	0.19	0.19	19
A28	Etihad Airways	6.34	20.27	22.28	77.72	2.48	6.23	10.37	34.74	0.20	0.19	0.19	20
A78	Vistara	6.65	19.86	23.67	76.33	2.75	6.37	11.02	34.19	0.22	0.20	0.21	21
A18	Bangkok Airways	6.82	19.88	23.98	76.02	2.59	6.68	11.13	34.20	0.22	0.20	0.21	22
A36	Gulf Air	6.87	19.78	24.26	75.74	2.83	6.68	11.32	34.07	0.22	0.21	0.22	23
A37	Hainan Airlines	7.01	19.63	24.97	75.03	2.85	6.15	11.61	33.60	0.23	0.22	0.22	24
A52	Lufthansa	7.23	19.48	25.62	74.38	2.93	6.68	11.93	33.51	0.24	0.22	0.23	25
A68	Southwest Airlines	8.85	17.44	32.99	67.01	3.19	5.26	15.01	29.90	0.32	0.31	0.31	26
A9	AirAsia	9.66	17.16	34.84	65.15	3.99	5.93	16.16	29.42	0.34	0.33	0.34	27
A65	Scoot	9.83	17.02	35.18	64.82	4.15	5.40	16.39	29.08	0.35	0.33	0.34	28
A14	Asiana Airlines	9.88	16.66	36.57	63.42	3.41	5.37	16.62	28.49	0.36	0.35	0.35	29
A80	WestJet	10.09	16.75	36.62	63.38	4.16	5.40	16.96	28.51	0.36	0.35	0.36	30
A64	Saudi Arabian Airlines	10.23	16.64	37.17	62.83	4.21	5.93	17.20	28.47	0.37	0.35	0.36	31
A31	Fiji Airways	10.09	16.41	37.63	62.37	3.45	5.40	17.06	28.06	0.37	0.36	0.36	32
A15	Austrian Airlines	10.31	16.34	37.67	62.33	4.43	5.40	17.47	28.02	0.38	0.36	0.37	33
A27	Ethiopian Airlines	10.52	15.89	39.17	60.83	3.90	5.20	17.86	27.31	0.39	0.38	0.38	34
A7	Air New Zealand	10.67	15.69	40.17	59.83	3.87	5.40	18.24	26.97	0.40	0.39	0.39	35
A62	Ryanair	10.68	15.71	40.10	59.90	4.08	5.17	18.29	26.93	0.40	0.39	0.39	36
A1	Aegean Airlines	11.07	15.55	41.00	59.00	4.12	5.31	18.73	26.62	0.41	0.40	0.40	37
A4	Air Astana	11.19	15.34	41.82	58.17	4.16	5.40	19.06	26.30	0.42	0.40	0.41	38
A54	Oman Air	11.67	14.67	43.94	56.06	3.90	4.92	19.84	25.22	0.44	0.43	0.43	39
A35	Garuda Indonesia	11.64	14.75	43.95	56.05	4.06	4.96	19.88	25.25	0.44	0.43	0.43	40
A79	Vueling Airlines	13.85	12.53	52.78	47.22	4.57	4.08	23.74	21.28	0.54	0.53	0.53	41
A44	JetBlue Airways	14.37	12.38	53.95	46.05	5.22	4.13	24.52	20.85	0.56	0.54	0.55	42
A5	Air Canada	14.77	11.70	56.35	43.65	4.91	4.25	25.34	19.87	0.58	0.57	0.57	43
A17	Azul Airlines	14.76	11.59	56.40	43.60	4.78	4.25	25.31	19.81	0.58	0.57	0.57	44
A25	EasyJet	14.76	11.58	56.40	43.59	5.01	4.13	25.39	19.77	0.58	0.57	0.57	45
A53	Malaysia Airlines	15.09	11.53	57.08	42.92	5.40	4.25	25.85	19.57	0.59	0.57	0.58	46
A22	China Airlines	15.31	11.32	57.71	42.29	5.85	4.08	26.29	19.23	0.60	0.58	0.59	47
A77	Virgin Australia	15.32	11.25	58.22	41.78	5.17	4.25	26.24	19.09	0.60	0.59	0.59	48
A75	Vietnam Airlines	15.80	10.91	59.75	40.25	5.50	3.98	27.01	18.38	0.62	0.60	0.61	49
A50	LATAM	15.85	10.74	60.27	39.73	5.28	3.89	27.13	18.12	0.62	0.61	0.62	50
A61	Royal Brunei Airlines	16.07	10.48	61.02	38.98	5.28	3.98	27.46	17.81	0.63	0.62	0.62	51
A2	Aer Lingus	16.35	10.31	61.84	38.16	5.40	4.08	27.86	17.51	0.64	0.63	0.63	52
A72	Thai Airways	16.39	10.19	61.99	38.01	5.85	3.55	28.08	17.25	0.65	0.63	0.64	53
A16	Azerbaijan Airlines	16.61	9.75	63.66	36.34	5.32	3.88	28.53	16.66	0.66	0.65	0.65	54
A41	IndiGo	16.67	9.68	63.51	36.49	5.66	3.61	28.61	16.59	0.66	0.65	0.65	55
A34	Flynas	18.63	7.58	71.66	28.34	5.68	2.57	31.99	12.83	0.74	0.74	0.74	56
A39	Hong Kong Airlines	18.85	7.48	72.40	27.60	5.69	3.17	32.31	12.75	0.75	0.75	0.75	57
A45	Jetstar Airways	18.98	7.51	72.81	27.19	5.81	2.89	32.53	12.53	0.76	0.75	0.75	58
A69	SunExpress	19.16	7.43	73.34	26.65	6.78	2.83	33.09	12.30	0.77	0.76	0.76	59
A43	Jet2 Airlines	19.56	7.43	74.27	25.73	6.98	2.89	33.60	12.01	0.78	0.76	0.77	60
A38	Hawaiian Airlines	19.51	7.15	74.68	25.32	6.50	2.83	33.56	11.77	0.78	0.77	0.78	61
A29	Eurowings	19.87	6.58	76.26	23.74	6.33	2.84	34.15	11.05	0.80	0.79	0.79	62
A63	SAS Scandinavian	19.94	6.47	76.64	23.36	6.03	2.71	34.20	10.85	0.80	0.79	0.80	63
A71	TAP Portugal	20.09	6.64	77.07	22.93	6.14	2.84	34.43	10.80	0.81	0.80	0.80	64
A60	Royal Air Maroc	20.15	6.48	77.06	22.94	6.51	2.76	34.57	10.73	0.81	0.80	0.80	65
A11	Alaska Airlines	20.42	5.99	78.61	21.39	6.51	2.46	35.18	9.95	0.82	0.82	0.82	66
A74	United Airlines	20.66	6.12	79.10	20.90	6.31	2.83	35.36	9.95	0.83	0.82	0.82	67
A12	American Airlines	20.68	6.12	79.37	20.63	6.29	2.83	35.44	9.86	0.83	0.82	0.83	68
A10	airBaltic	20.95	6.03	79.95	20.05	6.50	2.60	35.80	9.56	0.84	0.83	0.83	69
A55	Peach	20.92	5.83	80.04	19.96	6.78	2.51	35.91	9.43	0.84	0.83	0.84	70
A8	Air Transat	23.17	3.41	89.38	10.62	6.74	1.58	39.76	5.21	0.94	0.94	0.94	71
A51	LOT Polish	23.16	3.20	89.36	10.63	7.07	1.38	39.86	5.07	0.94	0.94	0.94	72
A46	Jetstar Asia	23.34	3.11	90.05	9.95	6.88	1.56	40.09	4.87	0.95	0.94	0.95	73
A56	Philippine Airlines	23.74	2.89	91.48	8.52	7.26	1.56	40.83	4.32	0.97	0.96	0.96	74
A59	Rex Airlines	23.82	2.95	91.55	8.45	7.26	1.42	40.88	4.27	0.97	0.96	0.96	75
A33	flyDubai	23.82	2.86	91.75	8.25	7.26	1.58	40.94	4.23	0.97	0.96	0.97	76
A49	Kuwait Airways	23.93	2.74	92.39	7.61	6.91	1.43	41.07	3.93	0.97	0.97	0.97	77
A20	Brussels Airlines	23.95	2.62	92.45	7.54	7.05	1.42	41.15	3.86	0.98	0.97	0.97	78
A67	South African Airways	24.31	2.43	93.63	6.36	7.07	1.46	41.67	3.42	0.99	0.98	0.99	79
A3	Air Arabia	24.56	1.87	94.92	5.08	6.90	1.13	42.13	2.69	1.00	1.00	1.00	80

by this method have been found to be stable and accurately reflect the comparative service quality across various airlines.

In comparison to other traditional MCDM models, our comprehensive model offers distinct advantages. It not only incorporates text mining as a data source but also delineates hierarchies among the evaluated alternatives. This hierarchical structure facilitates the evaluation of entities whose relative rankings may not be initially apparent. The application of this methodology enables the derivation of stable rankings in a variety of fields, including the hotel industry (Berezina et al., 2016) and the supply chain sector (Lim et al., 2021).

Nevertheless, it is crucial to acknowledge the limitations and challenges of these methodologies. A notable constraint of text mining is its potential inability to fully grasp the subtleties and context of natural language, including sarcasm and humor (Gupta et al., 2020; Kumar

Table 10
Ranking of airline service quality.

Ranking	Number	Airline	Ranking	Number	Airline
1	A26	Emirates	=41	A5	Air Canada
2	A73	Turkish Airlines	=41	A17	Azul Airlines
3	A70	Swiss International Air Lines	=43	A44	JetBlue Airways
=4	A6	Air France	=43	A53	Malaysia Airlines
=4	A13	ANA All Nippon Airways	=45	A77	Virgin Australia
=4	A42	Japan Airlines	=45	A79	Vueling Airlines
=4	A48	Korean Air	47	A25	EasyJet
=4	A58	Qatar Airways	48	A22	China Airlines
=4	A57	Qantas Airways	49	A2	Aer Lingus
10	A66	Singapore Airlines	50	A75	Vietnam Airlines
=11	A21	Cathay Pacific Airways	51	A61	Royal Brunei Airlines
=11	A23	China Southern Airlines	52	A50	LATAM
13	A47	KLM Royal Dutch Airlines	=53	A16	Azerbaijan Airlines
14	A30	EVA Air	=53	A41	IndiGo
=15	A18	Bangkok Airways	=53	A72	Thai Airways
=15	A36	Gulf Air	56	A39	Hong Kong Airlines
17	A52	Lufthansa	57	A45	Jetstar Airways
18	A19	British Airways	58	A34	Flynas
=19	A32	Finnair	59	A43	Jet2 Airlines
=19	A40	Iberia	60	A69	SunExpress
=21	A24	Delta Air Lines	=61	A29	Eurowings
=21	A28	Etihad Airways	=61	A38	Hawaiian Airlines
=21	A78	Vistara	=61	A71	TAP Portugal
=24	A37	Hainan Airlines	=64	A12	American Airlines
=24	A76	Virgin Atlantic	=64	A60	Royal Air Maroc
=26	A9	AirAsia	=64	A63	SAS Scandinavian
=26	A64	Saudi Arabian Airlines	=64	A74	United Airlines
28	A68	Southwest Airlines	=68	A10	airBaltic
=29	A31	Fiji Airways	=68	A11	Alaska Airlines
=29	A65	Scoot	70	A55	Peach
=29	A80	WestJet	71	A8	Air Transat
=32	A14	Asiana Airlines	72	A33	flyDubai
=32	A15	Austrian Airlines	73	A51	LOT Polish
34	A7	Air New Zealand	=74	A46	Jetstar Asia
35	A4	Air Astana	=74	A56	Philippine Airlines
36	A27	Ethiopian Airlines	76	A49	Kuwait Airways
37	A1	Aegean Airlines	=77	A59	Rex Airlines
38	A62	Ryanair	=77	A67	South African Airways
=39	A35	Garuda Indonesia	=79	A3	Air Arabia
=39	A54	Oman Air	=79	A20	Brussels Airlines

Table 11
Results of sensitivity analysis.

Robustness test statistic	Spearman's ρ	Kendall's τ	Kruskal–Wallis test p
Value	0.998	0.997	0.94

et al., 2021; Ashtiani and Raahemi, 2023). This could impact the precision and efficacy of topic and sentiment extraction. Furthermore, the subjectivity and biases of customers, influenced by personal expectations, emotions, or other factors (Hassani et al., 2020; Kushwaha et al., 2021), may influence the objective representation of service quality. Therefore, a cautious and critical approach is essential in interpreting and generalizing these findings to attain a more comprehensive and reliable understanding of airline service quality.

6. Conclusion

In this study, we have devised a comprehensive model for assessing airline service quality, utilizing the LSA-TOPSIS-VIKOR-AISM methodology. This comprehensive framework commences with the extraction of online review data from various platforms, subsequently assigning sentiment scores to each review. Our analysis delves into the utility, Euclidean distance, and individual regret metrics for each airline, culminating in the derivation of ranked trade-off solutions. Furthermore, we employ the AISM approach to meticulously examine a multitude of indicators, thereby facilitating the generation of directed topological hierarchical graphs. The empirical evidence indicates that our proposed method is characterized by robust data integrity, streamlined computations, and cogent conclusions, rendering it an exemplary tool for a comprehensive evaluation of service quality or performance.

Our research illuminates the fusion of two burgeoning technologies – text mining and sentiment analysis – with the MCDM model. This fusion harnesses the strengths of both to enhance the evaluation of airline service quality. It also effectively captures consumer intentions in a comprehensive manner. Future inquiries might expand to encompass a broader array of airlines, a wider range of service indicators, more extensive data sets, or the amalgamation with other methodologies, such as machine learning (Liao et al., 2023) and complex networks (Karczmarczyk et al., 2021). The distribution coefficient k utilized in our trade-off solution calculations is reflective of the opinions of specific airline professionals. However, it may not entirely align with the general public's preferences in airline decision-making. The incorporation of prospect theory (Zhao et al., 2022) and the construction of a value function based on multiple mental accounts provides avenues for future research into the variability of k under diverse scenarios.

CRediT authorship contribution statement

Haotian Xie: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Yi Li:** Writing – review & editing, Software, Methodology, Formal analysis, Data curation. **Yang Pu:** Writing – review & editing, Visualization, Software, Methodology. **Chen Zhang:** Writing – review & editing, Visualization, Validation, Software. **Junlin Huang:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Antons, D., Grünwald, E., Cichy, P., Salge, T.O., 2020. The application of text mining methods in innovation research: current state, evolution patterns, and development priorities. R & D Manage. 50 (3), 329–351. http://dx.doi.org/10.1111/radm.12408.

Ashtiani, M.N., Raahemi, B., 2023. News-based intelligent prediction of financial markets using text mining and machine learning: A systematic literature review. Expert Syst. Appl. 217, 119509. http://dx.doi.org/10.1016/j.eswa.2023.119509.

Baccianella, S., Esuli, A., Sebastiani, F., et al., 2010. Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining.. In: Lrec, vol. 10, no. 2010, pp. 2200–2204.

Badanik, B., Remenysegova, R., Kazda, A., 2023. Sentimental approach to airline service quality evaluation. Aerospace 10 (10), 883. http://dx.doi.org/10.3390/aerospace10100883.

Baisya, R.K., Sarkar, R., 2004. Customer satisfaction in the service sector: a case study of the airline industry. J. Adv. Manag. Res. http://dx.doi.org/10.1108/97279810480000366.

Bakır, M., Atalık, Ö., 2021. Application of fuzzy AHP and fuzzy MARCOS approach for the evaluation of e-service quality in the airline industry. Decis. Mak.: Appl. Manag. Eng. 4 (1), 127–152. http://dx.doi.org/10.31181/dmame2104127b.

Bellizzi, M.G., Eboli, L., Mazzulla, G., 2020. An online survey for the quality assessment of airlines' services. Res. Transp. Bus. Manag. 37, 100515.

Berezina, K., Bilgihan, A., Cobanoglu, C., Okumus, F., 2016. Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews. J. Hosp. Mark. Manag. 25 (1), 1–24. http://dx.doi.org/10.1080/19368623.2015.983631.

Berry, M.W., Dumais, S.T., O'Brien, G.W., 1995. Using linear algebra for intelligent information retrieval. SIAM Rev. 37 (4), 573–595. http://dx.doi.org/10.1137/1037127.

Biao, N., Wei, H., 2020. Extensibility evaluation model of military training methods based on adversarial interpretive structure model. Mil. Oper. Res. Syst. Eng. 34 (02), 46–51.

Bogicevic, V., Yang, W., Bujisic, M., Bilgihan, A., 2017. Visual data mining: Analysis of airline service quality attributes. J. Qual. Assur. Hosp. Tourism 18 (4), 509–530. http://dx.doi.org/10.1080/1528008X.2017.1314799.

Chatterjee, S., Ghatak, A., Nikte, R., Gupta, S., Kumar, A., 2022. Measuring SERVQUAL dimensions and their importance for customer-satisfaction using online reviews: a text mining approach. J. Enterp. Inf. Manag. 36 (1), 22–44. http://dx.doi.org/10.1108/JEIM-06-2021-0252.

Chen, C.F., 2008. Investigating structural relationships between service quality, perceived value, satisfaction, and behavioral intentions for air passengers: Evidence from Taiwan. Transp. Res. A 42 (4), 709–717. http://dx.doi.org/10.1016/j.tra.2008.01.007.

Chen, F.Y., Chang, Y.H., 2005. Examining airline service quality from a process perspective. J. Air Transp. Manag. 11 (2), 79–87. http://dx.doi.org/10.1016/j.jairtraman.2004.09.002.

Chen, S.J., Hwang, C.L., 1992. Fuzzy multiple attribute decision making methods. In: Fuzzy Multiple Attribute Decision Making. Springer, pp. 289–486. http://dx.doi.org/10.1007/978-3-642-46768-4_5.

Das, D., Datta, A., Kumar, P., Kazancoglu, Y., Ram, M., 2022. Building supply chain resilience in the era of COVID-19: An AHP-DEMATEL approach. Oper. Manag. Res. 15 (1), 249–267. http://dx.doi.org/10.1007/s12063-021-00200-4.

Duncan, E., Fanderl, H., Freundt, T., Maechler, N., Neher, K., 2017. Customer Experience: New Capabilities, New Audiences, New Opportunities. McKinsey & Company.

Elliott, K.M., Roach, D.W., 1993. Service quality in the airline industry: are carriers getting an unbiased evaluation from consumers? J. Prof. Serv. Mark. 9 (2), 71–82. http://dx.doi.org/10.1300/J090v09n02_06.

Eshkevari, M., Rezaee, M.J., Saberi, M., Hussain, O.K., 2022. An end-to-end ranking system based on customers reviews: Integrating semantic mining and MCDM techniques. Expert Syst. Appl. 209, 118294. http://dx.doi.org/10.1016/j.eswa.2022.118294.

Gilbert, D., Wong, R.K., 2003. Passenger expectations and airline services: a Hong Kong based study. Tour. Manag. 24 (5), 519–532. http://dx.doi.org/10.1016/S0261-5177(03)00002-5.

Gourdin, K.N., 1988. Bringing quality back to commercial air travel. Transp. J. 23–29.

Gul, M., 2018. A review of occupational health and safety risk assessment approaches based on multi-criteria decision-making methods and their fuzzy versions. Hum. Ecol. Risk Assess. Int. J. 24 (7), 1723–1760. http://dx.doi.org/10.1080/10807039.2018.1424531.

Gupta, A., Dengre, V., Kheruwala, H.A., Shah, M., 2020. Comprehensive review of text-mining applications in finance. Financ. Innov. 6 (1), 1–25. http://dx.doi.org/10.1186/s40854-020-00205-1.

Gursoy, D., Chen, M.H., Kim, H.J., 2005. The US airlines relative positioning based on attributes of service quality. Tour. Manag. 26 (1), 57–67. http://dx.doi.org/10.1016/j.tourman.2003.08.019.

Haghighat, N., 2017. Airline service quality evaluation: A review on concepts and models. Econ. Manag. Sustain. 2 (2), 31–47.

Hashemkhani Zolfani, S., Derakhti, A., 2020. Synergies of text mining and multiple attribute decision making: a criteria selection and weighting system in a prospective MADM outline. Symmetry 12 (5), 868. http://dx.doi.org/10.3390/sym12050868.

Hassani, H., Beneki, C., Unger, S., Mazinani, M.T., Yeganegi, M.R., 2020. Text mining in big data analytics. Big Data Cogn. Comput. 4 (1), 1. http://dx.doi.org/10.3390/bdcc4010001.

Hu, K.C., Hsiao, M.W., 2016. Quality risk assessment model for airline services concerning Taiwanese airlines. J. Air Transp. Manag. 53, 177–185. http://dx.doi.org/10.1016/j.jairtraman.2016.03.006.

Huang, Y.K., 2010. The effect of airline service quality on passengers' behavioural intentions using SERVQUAL scores: A Taiwan case study. J. East. Asia Soc. Transp. Stud. 8, 2330–2343. http://dx.doi.org/10.11175/easts.8.2330.

Hwang, C.L., Yoon, K., 1981. Methods for multiple attribute decision making. In: Multiple Attribute Decision Making. Springer, pp. 58–191. http://dx.doi.org/10.1007/978-3-642-83555-1_5.

Jiang, H., Zhang, Y., 2016. An investigation of service quality, customer satisfaction and loyalty in China's airline market. J. Air Transp. Manag. 57, 80–88. http://dx.doi.org/10.1016/j.jairtraman.2016.07.008.

Jo, T., 2019. Text Mining, vol. 45, Springer.

Karczmarczyk, A., Jankowski, J., Wkatrobski, J., 2021. Multi-criteria seed selection for targeting multi-attribute nodes in complex networks. Symmetry 13 (4), 731. http://dx.doi.org/10.3390/sym13040731.

Kramer, O., Kramer, O., 2016. Scikit-learn. Mach. Learn. Evol. Strateg. 45–53. http://dx.doi.org/10.1007/978-3-319-33383-0_5.

Kumar, S., Kar, A.K., Ilavarasan, P.V., 2021. Applications of text mining in services management: A systematic literature review. Int. J. Inf. Manag. Data Insights 1 (1), 100008. http://dx.doi.org/10.1016/j.jjimei.2021.100008.

Kushwaha, A.K., Kar, A.K., Dwivedi, Y.K., 2021. Applications of big data in emerging management disciplines: A literature review using text mining. Int. J. Inf. Manag. Data Insights 1 (2), 100017. http://dx.doi.org/10.1016/j.jjimei.2021.100017.

Laming, C., Mason, K., 2014. Customer experience—an analysis of the concept and its performance in airline brands. Res. Transp. Bus. Manag. 10, 15–25. http://dx.doi.org/10.1016/j.rtbm.2014.05.004.

Leon, S., Martín, J.C., 2020. A fuzzy segmentation analysis of airline passengers in the US based on service satisfaction.. Res. Transp. Bus. Manag. 37, 100550. http://dx.doi.org/10.1016/j.rtbm.2020.100550.

Li, G., 2017. Application of Sentiment Analysis: Assessing the Reliability and Validity of the Global Airlines Rating Program (B.S. thesis). University of Twente.

Li, Y., Tan, Y., Pu, Y., Zhu, Y., Xie, H., 2023. Exploring the drivers of green supply chain management in the Chinese electronics industry: Evidence from a GDEMATEL–AISM approach. Clean. Logist. Supply Chain (ISSN: 2772-3909) 7, 100110. http://dx.doi.org/10.1016/j.clscn.2023.100110.

Liao, H., He, Y., Wu, X., Wu, Z., Bausys, R., 2023. Reimagining multi-criterion decision making by data-driven methods based on machine learning: A literature review. Inf. Fusion 101970. http://dx.doi.org/10.1016/j.inffus.2023.101970.

Lim, M.K., Li, Y., Song, X., 2021. Exploring customer satisfaction in cold chain logistics using a text mining approach. Ind. Manag. Data Syst. 121 (12), 2426–2449. http://dx.doi.org/10.1108/IMDS-05-2021-0283.

Liou, J.J., Tzeng, G.-H., 2007. A non-additive model for evaluating airline service quality. J. Air Transp. Manag. 13 (3), 131–138. http://dx.doi.org/10.1016/j.rtbm.2020.100515.

Loper, E., Bird, S., 2002. Nltk: The natural language toolkit. http://dx.doi.org/10.48550/arXiv.cs/0205028, arXiv preprint cs/0205028.

Loria, S., et al., 2018. Textblob documentation. Release 0.15 2 (8), 269.

Lucini, F.R., Tonetto, L.M., Fogliatto, F.S., Anzanello, M.J., 2020. Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. J. Air Transp. Manag. 83, 101760. http://dx.doi.org/10.1016/j.jairtraman.2019.101760.

Mejia, J., Mankad, S., Gopal, A., 2021. Service quality using text mining: Measurement and consequences. Manuf. Serv. Oper. Manag. 23 (6), 1354–1372. http://dx.doi.org/10.1287/msom.2020.0883.

Mousavi, S., Bossink, B., 2020. Corporate-NGO partnership for environmentally sustainable innovation: Lessons from a cross-sector collaboration in aviation biofuels. Environ. Innov. Soc. Transit. 34, 80–95. http://dx.doi.org/10.1016/j.eist.2019.12.005.

Muzumdar, P., Kurian, G., Basyal, G.P., 2024. A Latent Dirichlet Allocation (LDA) semantic text analytics approach to explore topical features in charity crowdfunding campaigns. http://dx.doi.org/10.48550/arXiv.2401.02988, arXiv preprint arXiv:2401.02988.

Namukasa, J., 2013. The influence of airline service quality on passenger satisfaction and loyalty: The case of Uganda airline industry. TQM J. http://dx.doi.org/10.1108/TQM-11-2012-0092.

Opricovic, S., 1998. Multicriteria optimization of civil engineering systems. Fac. Civ. Eng., Belgrade 2 (1), 5–21.

Opricovic, S., Tzeng, G.-H., 2004. Compromise solution by MCDM methods: A comparative analysis of vikor and TOPSIS. European J. Oper. Res. 156 (2), 445–455. http://dx.doi.org/10.1016/S0377-2217(03)00020-1.

Ostrowski, P.L., O'Brien, T.V., Gordon, G.L., 1993. Service quality and customer loyalty in the commercial airline industry. J. Travel Res. 32 (2), 16–24. http://dx.doi.org/10.1177/004728759303200203.

Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1985. A conceptual model of service quality and its implications for future research. J. Mark. 49 (4), 41–50. http://dx.doi.org/10.1177/002224298504900403.

Parasuraman, A., Zeithaml, V.A., Berry, L., 1988. SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality 64(1). pp. 12–40.

Park, J., 2023. Combined text-mining/DEA method for measuring level of customer satisfaction from online reviews. Expert Syst. Appl. 120767. http://dx.doi.org/10.1016/j.eswa.2023.120767.

Park, S., Lee, J.S., Nicolau, J.L., 2020. Understanding the dynamics of the quality of airline service attributes: Satisfiers and dissatisfiers. Tour. Manag. 81, 104163. http://dx.doi.org/10.1016/j.tourman.2020.104163.

Park, J.W., Robertson, R., Wu, C.L., 2004. The effect of airline service quality on passengers' behavioural intentions: a Korean case study. J. Air Transp. Manag. (ISSN: 0969-6997) 10 (6), 435–439. http://dx.doi.org/10.1016/j.jairtraman.2004.06.001.

Prelec, D., Seung, H.S., McCoy, J., 2017. A solution to the single-question crowd wisdom problem. Nature 541 (7638), 532–535. http://dx.doi.org/10.1038/nature21054.

Richardson, L., 2007. Beautiful soup documentation.

Robledo, M.A., 2001. Measuring and managing service quality: integrating customer expectations. Manag. Serv. Qual. Int. J. http://dx.doi.org/10.1108/09604520110379472.

Sahoo, S.K., Goswami, S.S., 2023. A comprehensive review of multiple criteria decision-making (MCDM) methods: advancements, applications, and future directions. Decis. Mak. Adv. 1 (1), 25–48. http://dx.doi.org/10.31181/dma1120237.

Sezgen, E., Mason, K.J., Mayer, R., 2019. Voice of airline passenger: A text mining approach to understand customer satisfaction. J. Air Transp. Manag. 77, 65–74. http://dx.doi.org/10.1016/j.jairtraman.2019.04.001.

Shadiyar, A., Ban, H.J., Kim, H.S., 2020. Extracting key drivers of air passenger's experience and satisfaction through online review analysis. Sustainability 12 (21), 9188. http://dx.doi.org/10.3390/su12219188.

Shah, A.M., Yan, X., Tariq, S., Khan, S., 2021. Listening to the patient voice: using a sentic computing model to evaluate physicians' healthcare service quality for strategic planning in hospitals. Qual. Quant. 55, 173–201. http://dx.doi.org/10.1007/s11135-020-00999-3.

Singh, S.P., Adhikari, A., Majumdar, A., Bisi, A., 2022. Does service quality influence operational and financial performance of third party logistics service providers? A mixed multi criteria decision making-text mining-based investigation. Transp. Res. E 157, 102558. http://dx.doi.org/10.1016/j.tre.2021.102558.

Sotoudeh-Anvari, A., 2022. The applications of MCDM methods in COVID-19 pandemic: A state of the art review. Appl. Soft Comput. 109238. http://dx.doi.org/10.1016/j.asoc.2022.109238.

Taherdoost, H., Madanchian, M., 2023. Multi-criteria decision making (MCDM) methods and concepts. Encyclopedia 3 (1), 77–87. http://dx.doi.org/10.3390/encyclopedia3010006.

Thokala, P., Devlin, N., Marsh, K., Baltussen, R., Boysen, M., Kalo, Z., Longrenn, T., Mussen, F., Peacock, S., Watkins, J., et al., 2016. Multiple criteria decision analysis for health care decision making—an introduction: report 1 of the ISPOR MCDA emerging good practices task force. Value Health 19 (1), 1–13. http://dx.doi.org/10.1016/j.jval.2015.12.003.

Tian, X., He, W., Tang, C., Li, L., Xu, H., Selover, D., 2020. A new approach of social media analytics to predict service quality: evidence from the airline industry. J. Enterp. Inf. Manag. 33 (1), 51–70. http://dx.doi.org/10.1108/JEIM-03-2019-0086.

Truitt, L.J., Haynes, R., 1994. Evaluating service quality and productivity in the regional airline industry. Transp. J. 21–32.

Vencovskỳ, F., 2020. Service quality evaluation using text mining: A systematic literature review. In: Perspectives in Business Informatics Research: 19th International Conference on Business Informatics Research, BIR 2020, Vienna, Austria, September 21–23, 2020, Proceedings 19. Springer, pp. 159–173.

Wagire, A.A., Rathore, A., Jain, R., 2020. Analysis and synthesis of Industry 4.0 research landscape: Using latent semantic analysis approach. J. Manuf. Technol. Manag. 31 (1), 31–51. http://dx.doi.org/10.1108/JMTM-10-2018-0349.

Yoon, K., 1987. A reconciliation among discrete compromise solutions. J. Oper. Res. Soc. 38 (3), 277–286. http://dx.doi.org/10.1057/jors.1987.44.

Zeithaml, V.A., Parasuraman, A., Berry, L.L., Berry, L.L., 1990. Delivering Quality Service: Balancing Customer Perceptions and Expectations. Simon and Schuster.

Zhao, M., Shen, X., Liao, H., Cai, M., 2022. Selecting products through text reviews: An MCDM method incorporating personalized heuristic judgments in the prospect theory. Fuzzy Optim. Decis. Mak. 1–24. http://dx.doi.org/10.1007/s10700-021-09359-8.